THE DYNAMICS OF INDIVIDUALS' FAT CONSUMPTION

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Consumers are increasingly aware of the link between their lifestyle choices and the risk of noncommunicable diseases. A dynamic approach incorporating this linkage in food demand is developed, where consumers maximize utility over time by choosing fat intake to control their cumulative fat level. The resulting dynamic indirect utility function and household data on meat, fish, and dairy consumption are used to estimate a censored demand system. Results show that consumers consciously adjust, but not instantaneously, their cumulative fat level. Highly educated households have a faster rate of adjustment of cumulative fat. When cumulative fat level increases, consumers shift to dairy or white meat from red meat products.

Key words: dynamic utility function, food demand, health choice, household data.

In the past few decades, consumers have become increasingly aware of the link between their lifestyle choices and the risk of noncommunicable diseases such as heart ailments and cancer (Chern, Loehman, and Yen 1995; Cutler, Glaeser, and Shapiro 2003; Ippolito and Mathios 1995; Variyam et al. 1998). Several scientific studies have found an association between diet, physical activity, and health risks (Stoeckli and Keller 2004; van Dam et al. 2002; Giovannucci et al. 1993). These studies view the diet–health risk association as a result of consumption decisions of the past, present, and the future. For instance, van Dam et al. (2002) tracked over 40,000 people between 1986 and 1994 and found that frequent consumption of meat, a proxy for total and saturated fat intake, increases risk of type 2 diabetes. Others have identified significant correlations between total fat intake and incidences of several types of cancer (Stoeckli and Keller 2004). The diet–health risk association has prompted the U.S. Departments of Agriculture and Health and Human Services, American Cancer Society and others to issue dietary guidelines, which urge a change in the composition of fat intake from meat products to dairy and fish products.

Several factors make it difficult to incorporate health management into an optimizing framework in order to derive empirical specifications of health-based food demand functions. For instance, assuming consumers have access to some health information, it is not clear whether this information should be represented as a preference or constraint in an optimizing decision model. Moreover, recent health-based food consumption models are static, while a more realistic representation of a health optimization would require a dynamic model (Park and Davis 2001; Nayga and Capps 1999).

This article introduces a dynamic approach to incorporate health management in consumer's demand for meat, fish, and dairy (MFD) products. We derive MFD consumption from a two-step optimization problem. The first step consists of a utility maximization problem with two constraints: an expenditure constraint and a fat intake constraint. We assume that consumers earn positive utility from the consumption of foods (goods), even those with high fat content, but earn negative utility from their cumulative fat level (bads) in the body.[1] That is, consumers enjoy consuming fatty meats (steak, pizza) but are limited by self-imposed (or doctor-imposed) health requirements. Therefore, consumers face not

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[1] We recognize also that not all fats are bad and managed by consumers. Our theoretical set up can easily be adapted to most "bads" including fat. However, our empirical specification focuses on one such bads—fat, due to data availability.

only expenditure constraints but also constraints on the amount of fat they are willing to absorb each time period. The solution to the first-step problem is an indirect utility function (IUF) with properties not unlike those of the standard IUF. However, fat intake and the cumulative fat level are arguments of the IUF, in addition to prices and expenditures. In the second step, consumers maximize utility over time by regulating their fat intake in order to control the cumulative fat level. The choice of fat intake is presented as a dynamic optimization problem, whose solution is a dynamic IUF (DIUF). Using the duality properties of the DIUF (equivalents of Roy's Identity), we derive dynamic consumer demand functions with a law of motion incorporating health decisions.

A second-order approximation of the DIUF allows us to represent the dynamic demand functions as expenditure shares and to derive an explicit equation of motion for cumulative fat levels. They are estimated as a censored system using data on 250 U.S. households on a monthly basis between December 1997 and January 2001, which are obtained from AC-Nielsen's Homescan Panel (ACNH) database. The products included in our estimation are beef, pork, chicken, fish, milk, and cheese. The fat content of the MFD products is calculated using a recent report of the Agricultural Research Service, U.S. Department of Agriculture (Gebhardt and Thomas 2002). The price and expenditure elasticities of demand for various MFD products are computed using the estimates of the dynamic demand functions. To the best of our knowledge, this is the first study to identify how consumers adjust fat intake over time and to derive the effects of accumulated fat on demand for individual MFD products (elasticities).

A Dynamic Demand Model with Fat Intake

The first step in deriving dynamic consumer demand functions with health attributes is to set up an IUF, which represents the solution to a static two-constraint utility maximization problem. This problem can be specified as

$$(1) \quad \psi(p, f, E, F, C) = \max U(x_1, x_2, \ldots, x_n, C)$$

$$\text{s.t.} \sum_{i=1}^{n} p_i x_i \le E; \quad \sum_{i=1}^{n} f_i x_i = F$$

where ψ is the IUF, p is a nx1 vector of prices of consumption goods x, E is expenditures, $f_i \in f$

is the fat content of consumption good x_i, F and C are respectively fat intake and cumulative body fat level and U is a direct utility function.

The first constraint in equation (1) represents the typical expenditure constraint and is assumed to be binding. The second constraint represents a health or fat-intake constraint. Each food product contains a certain amount of fat (f_i), which is written as a proportion of the product's consumption in equation (1). For example, if f_1 were 0.01, it would mean that 1% of the amount of x_1 consumed is fat. The specification in equation (1) assumes that consumers care about the total fat intake rather than fat intake from individual foods, which allows for substitutability among "bads."[2] A special case of equation (1) is one where F and C are scalars implying that people care only about total fat and do not manage fat from each MFD product.

The utility function, U, is increasing and concave in the n goods, x_i, but decreasing in the amount of cumulative fat, C.[3] The properties of the static IUF are similar to those of a standard utility function. That is, ψ is decreasing and convex in prices p, increasing and concave in E, and homogenous of degree zero in p and E. Additionally, ψ is increasing and concave in F.[4] This reflects the assumption that consumers enjoy and would consume more fatty meats, if self- (or doctor-) imposed fat constraints did not limit such consumption. However, consumers earn negative utility from their total cumulative fat levels C. We assume that ψ is decreasing in C. This view is analogous (but opposite in sign) to the roles of investment and capital in production theory with adjustment costs (Epstein 1981; Vasavada and Chambers 1986).[5]

Similar to dynamic production models, the solution to the first (allocation) stage is then used to optimize over time the level of fat intake (F) and cumulative fat (C). To determine the level of "C" we introduce dynamics to the consumer problem through an equation of

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[2] A general specification would treat fat from each MFD product differently. The analytics of the general specification is similar to that outlined in the following.

[3] Note that $U(\cdot)$ may not be a function of C for some low-income consumers.

[4] Concavity applies since the structure of the fat constraint is similar to that of the expenditure constraint, and thus, F must influence the IUF in a way similar to E.

[5] Consider this in light of a production function with adjustment costs. Higher C (capital), lowers (raises) utility (output), but the process of consuming fatty goods and changing C (capital) raises (lowers) utility (output). These could be termed adjustment "benefits," which may prevent consumers from instantly adjusting to desired cumulative fat levels.

motion describing fat absorption in each period, $\dot{C}$

$$(2) \qquad \dot{C} = F - \gamma C$$

where γ is an average rate of fat decay in the body for all MFD products. The decay rate is determined by biological factors and assumed to be exogenous for our purposes.[6] We focus on fat absorption because of the scientific link between meat fat consumption and higher risks of noncommunicable diseases. In addition, the law of motion represents expected behavior of an average consumer based on dietary guidelines from health organizations. Evidence suggests that consumers choose food products based on fat content (Cowley 1998; Food Marketing Institute 2005).[7] Moreover, equation (2) represents a health management rule not unlike a body mass index in related studies (Cutler, Glaeser, and Shapiro 2003).

Note that health-conscious consumers face a dynamic problem analogous to a standard dynamic investment problem in production economics (Epstein 1981; Sargent 1978; Vasavada and Chambers 1986). While fat intake raises consumer utility each period, cumulative fat lowers utility. Consumers control C by managing F each period. That is, in each time period, consumers vary the amount and types of meat they consume to meet their optimal choice of F. So, cumulative fat follows an equation of motion and decays at the rate of γ. This choice problem can be represented as a standard dynamic optimization problem, where consumers maximize their indirect utility across time. The control variable is F, representing each period's fat intake, which is used to manage the state variable C. To focus our attention on fat intake, we do not specify an equation of motion for expenditures. This makes our dynamic demand functions dependent on expenditures rather than income in the following sections.

The dynamic problem to represent this consumer can be written as

$$(3)$$

$$V(p, f, E, C) = \max_{F} \int_{0}^{\infty} e^{-\alpha t} \psi(p, f, E, F, C)$$

$$\text{s.t. } \dot{C} = F - \gamma C$$

where V is a DIUF and α is a consumer's subjective time discount rate. In the dynamic problem in equation (3), a consumer manages his/her cumulative fat level, C, by choosing the level of fat intake each period, F, so as to maximize discounted utility over time. Since consumers enjoy fatty foods, a rise in F increases consumer's static utility, but the cumulative build up of fat, C, lowers long-run utility. The DIUF has prices, expenditures, and the fat content of each product, and total cumulative fat as its arguments.

As in any dynamic problem, there exists a Bellman equation, which is the static equivalent of the dynamic problem. The Bellman equation is given by

$$(4) \qquad \alpha V(p, f, E, C) = \max_{F} \psi(p, f, E, F, C)$$

$$+ V_C(F - \gamma C).$$

Equation (4) can be viewed as a typical Lagrangian problem, where the Lagrange multiplier (LM) is written explicitly in terms of the derivative of DIUF, i.e., V_C, which is the shadow price of the cumulative fat level C. The properties of $V(\cdot)$ are derived in the Appendix.

To specify a demand function consistent with the dynamic objective function in equation (3), the envelope properties of the DIUF must be derived. This can be done by setting up a primal-dual problem based on the Bellman equation as follows

$$(5) \qquad \min_{p, E, C} \{\alpha V(p, f, E, C) - \psi(p, f, E, F, C)$$

$$- V_C(F - \gamma C)\}.$$

The optimizing problem in equation (5) treats F as given and seeks to find a price vector (p), the level of E, and C that minimizes the difference between the optimal DIUF and the right-hand side of equation (4). In other words, the objective is to find a p, E, and C which make the F in equation (4) optimal. While it is possible to solve the optimization problem in equation (5), for the purposes of this article, the problem in equation (5) serves primarily to provide a basis for deriving dynamic demand functions, which are consistent with the maximization problem in equations (3) and

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[6] Again, in the general case where F and C are vectors, there will be n laws of motion. Equation (2) would then involve a Γ matrix, whose structure depends on the assumed adjustment process.

[7] A number of media, health publications, as well as doctors and nutritionists advise consumers to manage their meat consumption this way. Calorie management by consumers is a more recent trend, but how calories translate into fat and vice versa is beyond the scope of this study.

(4). Equation (5) is also used to determine the properties of the DIUF, which are presented in the Appendix. The DIUF is homogeneous of degree zero in prices and expenditures, is decreasing and convex in prices, increasing and concave in expenditures, and decreasing and concave in cumulative fat. For applications of the envelope theorem in dynamic optimization see Epstein (1981), and LaFrance and Barney (1991).

To derive the demand functions consistent with the DIUF, we obtain the first-order conditions for the problem in equation (5). These conditions are

$$\alpha V_{p_i} - \psi_{p_i} - V_{Cp_i}\dot{C} = 0 \ \forall i = 1, 2, \dots, n$$

$$(6) \quad \alpha V_E - \psi_E - V_{CE}\dot{C} = 0$$

$$\alpha V_C - \psi_C - V_{CC}\dot{C} + \gamma V_C = 0$$

where the subscripts p_i, E, and C represent derivatives with respect to prices, expenditures, and cumulative fat, respectively. For example V_{p_i} represents the derivative of the DIUF with respect to the ith output price. The three equalities in equation (6) are respectively the first-order conditions with respect to prices, expenditures, and C. They can be solved to obtain levels of p^*, E^*, and C^* that make whatever level of F, that is represented in equation (4) optimal.

To recover demand functions from equation (6), we need to rewrite them as

$$\alpha V_{p_i} - V_{Cp_i}\dot{C} = \psi_{p_i} \quad \forall i = 1, 2, \dots, n$$

$$(7) \quad \alpha V_E - V_{CE}\dot{C} = \psi_E$$

$$\dot{C} = \frac{(\alpha + \gamma)V_C - \psi_C}{V_{CC}}.$$

To obtain the demand function, divide the first line of equation (7) by its second line

$$(8)$$

$$x_i = \frac{\psi_{p_i}}{\psi_E} = \frac{\alpha V_{p_i} - V_{Cp_i}\dot{C}}{\alpha V_E - V_{CE}\dot{C}} \quad \forall i = 1, 2, \dots, n.$$

Equation (8) shows that it is possible to derive the dynamic demand function from derivatives of the DIUF function (equivalent to dynamic Roy's Identity). If it is possible to calculate the amount of MFD fats consumed each period, the derivatives of a particular specification of a value function yield the dynamic demand func-

tions. Note that the equation of motion for cumulative fat ($\dot{C}$) requires information on the derivatives of static and with dynamic.

The specification in equations (7) and (8) suggest two possible strategies for estimating health-based dynamic demand functions. One is to separately estimate demand functions and the cumulative fat motion ($\dot{C}$) equation, since together they form a recursive system. The second is to substitute the $\dot{C}$ equation directly into the consumer demand equations. If this latter course is taken then the demand function becomes

$$(9) \quad x_i = \frac{\alpha V_{p_i} + \frac{1}{V_{CC}}\left[((\alpha + \gamma)V_C - \psi_C)V_{Cp_i}\right]}{\alpha V_E + \frac{1}{V_{CC}}\left[((\alpha + \gamma)V_C - \psi_C)V_{CE}\right]}.$$

However, it will be shown later in this article that the structure of the residuals from equations (7) and (8) can result in a linear system of dynamic demand functions.

An Empirical Example

To obtain an empirical framework for the dynamic demand functions, we first specify the DIUF as a second-order quadratic approximation to a true function $V(\cdot)$

$$(10)$$

$$V(p, f, E, C) = \beta_0 + \sum_{i=1}^{n} \beta_i \tilde{p}_i + \delta_1 C + \lambda_1 \tilde{E}$$

$$+ \frac{1}{2}\sum_{i,j=1}^{n} \beta_{ij} \tilde{p}_i \tilde{p}_j + \frac{1}{2}\delta_2 C^2$$

$$+ \frac{1}{2}\lambda_2 \tilde{E}^2 + \sum_{i=1}^{n} \mu_i (\tilde{p}_i C)$$

$$+ \sum_{i=1}^{n} \pi_i (\tilde{p}_i \tilde{E}) + \rho(C\tilde{E})$$

where the "∼" over a variable indicates a logarithmic transformation. Note that only economic variables in equation (10) are specified in natural logarithms. The above approximation is similar to example 2 of Epstein (1981, p. 88).[8] The f_i terms, the fat content of each

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[8] In response to a question on whether solutions to functions of the form $\varphi(x, y) = f(x) + g(y) + h(x)k(y)$ exist, Lundberg (1992) derived several representatives of equivalence classes of solutions to $\varphi, f, g, h,$ and k. Our specification in equation (10) is a second-order approximation, which is linear in parameters and in the spirit of Lundberg (1992). It is important to emphasize here that most

product, are not explicitly specified in equation (10) because they do not change over time and therefore, are embodied in the constant term. Consumers are assumed to hold static food price expectations.

Given the above specification for the DIUF, the following derivatives apply

$$\alpha V_{p_i} = \frac{\alpha}{p_i} \left(\beta_i + \sum_{j=1}^{n} \beta_{ij} \tilde{p}_j + \mu_i C + \pi_i \tilde{E} \right)$$

$$\forall i = 1, 2, \ldots, n;$$

$$(11) \quad \alpha V_E = \frac{\alpha}{E} \left(\lambda_1 + \lambda_2 \tilde{E} + \sum_{i=1}^{n} \pi_i \tilde{p}_i + \rho C \right);$$

$$V_C = \delta_1 + \delta_2 C + \rho \tilde{E} + \sum_{i=1}^{n} \mu_i \tilde{p}_i$$

$$\forall i = 1, 2, \ldots., n;$$

$$V_{CE} = \frac{\rho}{E}; \quad V_{Cp_i} = \frac{\mu_i}{p_i}; \quad V_{CC} = \delta_2.$$

Therefore, the quantity demanded of the *i*th good can be written as

(12)

$$x_i = \frac{\alpha V_{p_i} - V_{Cp_i} \dot{C}}{\alpha V_E - V_{CE} \dot{C}}$$

$$= \frac{\frac{\alpha}{p_i} \left(\beta_i + \sum_{j=1}^{n} \beta_{ij} \tilde{p}_j + \mu_i C + \pi_i \tilde{E} \right) - \frac{\mu_i \dot{C}}{p_i}}{\frac{\alpha}{E} \left(\lambda_1 + \lambda_2 \tilde{E} + \sum_{i=1}^{n} \pi_i \tilde{p}_i + \rho C \right) - \frac{\rho \dot{C}}{E}}.$$

From equation (12), expenditure share equations for the *i*th good can be written as

(13)

$$s_i = \frac{p_i x_i}{E}$$

$$= \frac{\alpha \left(\beta_i + \sum_{j=1}^{n} \beta_{ij} \tilde{p}_j + \mu_i C + \pi_i \tilde{E} \right) - \mu_i \dot{C}}{\alpha \left(\lambda_1 + \lambda_2 \tilde{E} + \sum_{i=1}^{n} \pi_i \tilde{p}_i + \rho C \right) - \rho \dot{C}}$$

$$\forall i = 1, 2, \ldots, n$$

where s_i is the *i*th good's share of the total expenditures. Demand properties, homogeneity in $\tilde{p}$ and $\tilde{E}$ and adding up (shares sum to one),

hold if across all share equations (LaFrance 2001)

$$(14) \quad \sum_{i=1}^{n} \beta_i = 1; \quad \sum_{i=1}^{n} \beta_{ij} = \sum_{j=1}^{n} \beta_{ij} = \sum_{i=1}^{n} \mu_i$$

$$= \sum_{i=1}^{n} \pi_i = 0; \quad \lambda_1 = 1;$$

$$\lambda_2 = \rho = 0.$$

Imposing the homogeneity and adding up restrictions that apply to equation (12) yields the following share equation for the *i*th good

(15)

$$s_i = \frac{\alpha \left(\beta_i + \sum_{j=1}^{n} \beta_{ij} \tilde{p}_j + \mu_i C + \pi_i \tilde{E} \right) - \mu_i \dot{C}}{\alpha \left(1 + \sum_{i=1}^{n} \pi_i \tilde{p}_i \right)}.$$

Equation (15) shows that every share equation has the same denominator. In fact, with the exception of the terms containing C and $\dot{C}$ the share equations in equation (15) are not that different from standard Marshallian demands. If each $\mu_i = 0$, then equation (15) reduces to

$$(16) \quad s_i = \frac{\alpha \left(\beta_i + \sum_{j=1}^{n} \beta_{ij} \tilde{p}_j + \pi_i \tilde{E} \right)}{\alpha \left(1 + \sum_{i=1}^{n} \pi_i \tilde{p}_i \right)}.$$

Thus, nested within our health-based model is a Marshallian demand (share) function that is derived from Roy's identity. Using econometric methods it is possible to test parameter restrictions that collapse our health-based demand into a standard Marshallian demand function.

Similar to Marshallian demand, restrictions on price and income can be imposed to insure "Slutksy symmetry," i.e., the Slutksy matrices, which convert an income-based demand function (i.e., Marshallian, or those similar to equation (16)) to a Hicksian demand, are symmetric. In our equation (10) symmetry of the β_{ij} parameters is a necessary but not sufficient condition for "Slutksy" symmetry. Though not sufficient, we impose the symmetry of the β_{ij} parameters in the estimation of share equations (Appendix, Section II). An advantage of imposing adding-up restrictions is that it allows a linear representation of equation (15). If the shares sum to one, the numerator of equation (15) summed over *i* is equal to that of the denominator. Section II of the Appendix

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empirical studies use "a" particular second-order approximation meaning that there exists a number of solutions to the true function. Our specification (equation (10)) is one such solution to $\varphi, f, g, h,$ and k. See also Von Haefen (2002).

shows that this implies $\sum_{i=1}^{n} \pi_i p_i = 0$ and so, we have a linear share equation as follows

$$(17) \quad s_i = \beta_i + \sum_{j=1}^{n} \beta_{ij} \tilde{p}_j + \mu_i C + \pi_i \tilde{E} - \frac{\mu_i}{\alpha} \dot{C}.$$

In sum, equation (17) and the restrictions noted above (homogeneity, adding up, and Slutsky symmetry) provide a demand model that is consistent with both the standard consumer theory of choice and a dynamic food and health management model.

Equation of Motion

An advantage of our demand approach is that it allows joint estimation of the equation of motion $\dot{C}$. Using equations (7) and (10), the equation of motion for cumulative fat is given by

$$(18) \quad \dot{C} = \frac{(\alpha + \gamma)V_C - \psi_C}{V_{CC}}$$

$$= \frac{1}{\delta_2} \left[\left((\alpha + \gamma) \left(\delta_1 + \delta_2 C + \rho \tilde{E} \right. \right. \right.$$

$$\left. \left. \left. + \sum_{i=1}^{n} \mu_i \tilde{p}_i \right) \right) - \psi_C \right].$$

The specification of the DIUF or $V(\cdot)$ function alone is not sufficient to derive an equation of motion for cumulative fat. We make the assumption that $\psi_C = -\zeta C$ where ζ is a parameter to be estimated.[9] Substituting ψ_C into equation (18) gives us the reduced form $\dot{C}$ equation

$$(19) \quad \dot{C} = \frac{1}{\delta_2} \left[\left((\alpha + \gamma) \left(\delta_1 + \delta_2 C \right. \right. \right.$$

$$\left. \left. \left. + \rho \tilde{E} + \sum_{i=1}^{n} \mu_i \tilde{p}_i \right) \right) + \zeta C \right]$$

which is nonlinear in parameters. A linearized version of equation (19) is given by

$$(20) \quad \dot{C} = a_1 + a_2 C + a_3 \tilde{E} + \sum_{i=1}^{n} a_{4i} \tilde{p}_i$$

where $a_1 = \frac{\delta_1}{\delta_2}(\alpha + \gamma); a_2 = (\alpha + \gamma) + \frac{\zeta}{\delta_2}; a_3 = \frac{\rho}{\delta_2}; a_{4i} = \frac{\mu_i}{\delta_2}$. Some of the parameters of equation (19) can be identified using those of equation (20). Although some other parameters remain unidentified, the rate of adjustment of cumulative fat, a_2, can be obtained directly from equation (20). Linearizing (in parameters) the $\dot{C}$ equation affects neither the computation of price and expenditure elasticities nor the adjustment rate of C and cumulative fat effects on MFD demand as shown in the following sections.

Data

For implementing meat and dairy demand functions with fat intake, we utilized the ACNH database. The ACNH database reports households' purchases of food products, their prices and attributes along with demographic information. The database has been compiled since December 1997, but 2001 is the latest year for which data are available. Our product choice depended on data availability and included beef, pork, chicken, fish, milk, and cheese. They represent over 95% of all meat and dairy products consumption reported by participant households of the ACNH database. Our choice of time length depended on the frequency of zero purchases of participant households in the ACNH database. We chose monthly data since most consumers purchased milk products frequently, while meat and fish product purchases are infrequent.[10] Detailed prices are available, e.g., prices of different cuts of beef, milk price by percent fat content. We obtained aggregate prices for each of these commodities, by using a share-weighted average of sub-products' prices within a commodity.

The choice on households depended on households' participation or dropout rates in the ACNH database. For instance, a household participating in 1997/98 and abstaining in 2000 was excluded. Applying our product, time, and household choice criteria resulted in a final sample of 250 households, each of which had thirty-eight monthly observations

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[9] The assumption $\psi_C = -\zeta C$ should not be viewed as overly restrictive. Even if $\psi_C = -\zeta_C C + \zeta_E \tilde{E} + \sum_{i=1}^{n} \zeta_i \tilde{p}_i$, equation (19) becomes a bit more nonlinear. As noted in the text after equation (20), our specification of ψ_C doesn't affect the computation of price and expenditure elasticities, the adjustment rate of C, and the effects of C on food demand. A number of IUF specifications would be consistent with this derivative property.

[10] See also Food Marketing Institute (2005). Biweekly data contained zero purchases for almost all food products for over 60% of the sample period.

covering all of 1998–2000 and the last and first month of 1997 and 2001, respectively. For these 250 households, we obtained demographic information such as the household's size, and male and female education levels for use as conditioning variables in our estimation. Size is the number of people in a household, while education is an index taking on values 1–6 based on years of the schooling and degree/diploma. The use of the educational index assumes that for someone with level 6 education, we would expect that education was six times more important in food choices than for someone with level one education. To avoid this restriction, we introduced an additional variable on education: a dummy which takes value one when both male and female education indexes are equal to or greater than 4 (college education).

Fat intake is calculated using USDA's percent fat estimates of food products (Gebhardt and Thomas 2002). That is, the quantity of each of the meat and dairy products is multiplied by its respective (percent) fat content and the resulting term is summed over all products to obtain fat intake. While a common fat decay rate of 0.3 (parameter γ in equation (2)) is assumed for all households, distinct initial fat levels are set for each household. The household's initial fat level can be obtained using several, alternative methods. The common method to derive initial capital stock in the investment literature

is to divide the initial investment by its average growth rate over the sample period (e.g., Hall et al. 1988). Alternatively, each household's initial-period fat intake can be added to the average fat level of a representative household, where the latter is computed by cumulating fat intake over the first five periods. These alternative initial fat levels and their respective rates of change are highly correlated (correlation coefficient of 0.84). Since the choice on the decay rate and the method of computing initial fat level are subjective, we perform sensitivity analyses. The consumer's subjective discount rate, α, is assumed to equal 0.013 for monthly data, which translates to an annual discount rate of 0.16. We assume a relatively large discount rate to implicitly test whether consumers respond to fat accumulation even if they cared less about future consumption. Table 1 presents descriptive statistics of our household data.

Estimation Procedure

We face a number of econometric issues in the estimation of the dynamic demand system. Chief among them is the presence of zero consumption (table 1). Prior to addressing the zero-consumption issue, note that $\dot{C}$, an endogenous variable, is a regressor in the share

Table 1. Descriptive Statistics of Household Data (Monthly)

Variable Name	Unit	Mean	Standard Deviation	Share of Nonzero Observations (Percentage)
Expenditure shares				
Beef		0.3006	0.2293	80
Pork		0.1211	0.1555	64
Chicken		0.1852	0.2054	69
Fish		0.0128	0.0460	18
Cheese		0.0388	0.0596	67
Milk		0.3416	0.2393	91
Consumption quantity				
Beef	Pounds	8.554	8.025	
Pork	Pounds	3.634	5.538	
Chicken	Pounds	6.364	8.518	
Fish	Pounds	0.410	1.346	
Cheese	Pounds	1.228	1.669	
Milk	Pound-equivalents	22.149	18.919	
Expenditures	Dollars	176.4	116.4	
Male education	Index, 1–6	3.6800	1.6425	
Female education	Index, 1–6	3.8400	1.3291	
Household size	Number	2.7760	1.1857	

equations. In this context, instrumental variable estimators are often used to obtain consistent and efficient parameter estimates of the demand system. However, our system is recursive and so, parameter inconsistency of system estimators (e.g., generalized least squares [GLS]) arises only if the covariance between the error in the $\dot{C}$ and each share equation is not zero (Davidson and McKinnon 2004). Indeed, Breusch and Pagan's LM test failed to reject the hypothesis that the covariance between the errors of $\dot{C}$ and each share equation is zero. The calculated chi-squared test statistic (9.94) is below the critical value (25, 15 degrees of freedom) failing to reject the null of zero covariance at the 5% significance level. Note that the LM test did not reject zero covariance of errors within share equations.

Consistent estimation of a system of equations, when dependent variables are censored at zero, i.e., observing zero consumption of some products or at times, has received much attention in the demand literature. For each commodity, observed consumption is nonnegative, but the underlying "latent" variable is unrestricted since zero consumption is either intentional or due to random reasons. If a non-negligible proportion of consumption shares is negative, then it likely cannot be represented with a continuous distribution. A number of estimators have been proposed for consistent and efficient estimation of a censored demand system (e.g., Amemiya 1974; Wales and Woodland 1983; Lee and Pitt 1986). Two-step procedures have been employed in most household food demand studies (Heien and Wessels 1990; Hahn 1996). Shonkwiler and Yen (1999) demonstrate the inconsistency of a class of two-step estimators and suggest a way to correct them. However, the Shonkwiler and Yen (1999) estimator is subject to an inherent heteroskedasticity problem since the independent variables alone are transformed to obtain consistency. More recently, likelihood estimators including quasi- and simulated-likelihood procedures have been shown to be consistent and more efficient relative to two-step estimators commonly used in this literature (e.g., Yen, Lin, and Smallwood 2003; Dong and Kaiser 2005). Compounding the issue of which procedure to apply is that most of these estimators have only been developed for cross-sectional data, while their extension to panel settings awaits further research. Given the tradeoffs among procedures for censored dependent variables, we chose Shonkwiler and Yen's (1999) two-step (SYTS) estimator since

our demand system is derived from a dynamic setting and applied to panel data. The SYTS estimator is consistent and its correct covariance matrix can be obtained using Murphy and Topel's (1985) procedure as in Yen, Kan, and Su (2002).[11]

In the SYTS estimation procedure, for each commodity a dummy variable which takes on value one (zero) when consumption is positive (zero) is created. In the first step, each commodity-specific dummy is used as a dependent variable in a probit model with prices and expenditure as independent variables. For obtaining the correct covariance matrix as in Yen, Kan, and Su (2002), the number of regressors in the first-stage (probit) should equal that in the second stage (share equations). To ensure this equality, cross-products of prices and expenditure are used as additional regressors in the probit model, whose results are used to evaluate the probability and cumulative density at each data point.[12] The second step of the SYTS procedure involves estimation of the share (and $\dot{C}$) equations with two corrections: the independent variables are transformed using respective cumulative densities and the corresponding probability density is used as an additional regressor (equation (6), Shonkwiler and Yen 1999, p. 974). After these two corrections, procedures for the second-step estimation are no different than those for a noncensored system and include system GLS or seemingly unrelated regression (SUR) procedure. We chose a likelihood procedure (SUR) since it is required to adjust the covariance matrix of the second-step estimator.[13] Following Yen, Kan, and Su (2002, equation (16), p. 1801), the first and second derivatives of likelihood functions of both stages are evaluated using data and estimated parameters to derive an adjustment matrix to correct the second-step estimator's covariance matrix.

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[11] The SYTS procedure imposes the restriction that the latent shares sum to zero, but that restriction may not apply to observed shares. Following Yen, Lin, and Smallwood (2003), we estimate the first $n-1$ share equations and deduce the parameters of the nth equation using the budget identity $s_n = 1 - \sum_{i=1}^{n-1} s_i$. Dong and Kaiser (2005) impose the restriction that the latent and observed shares sum to one, but their likelihood procedure has not been extended to panel settings.
[12] Changes in the specification of the probit model had little quantitative effects on the second-stage results.
[13] We estimated the share and $\dot{C}$ equations using the SUR procedure assuming that the identified covariance between the errors of each share and $\dot{C}$ equation is zero. Our application of the Breusch–Pagan test detected the expenditure variable as the source of heteroskedasticity and so, our share and $\dot{C}$ equations are weighted using expenditures (Davidson and McKinnon 2004).

Prior to including zero consumption (shares) in the above estimation, we need to fill in their unobservable prices. There are several alternative methods to impute price when consumption is zero. Some studies, e.g., Lee and Pitt (1986), have used the underlying demand elasticity estimates to create a price high enough to force zero consumption. Others imputed missing prices with sample average or maximum (Yen, Lin, and Smallwood 2003). Perali and Chavas (2000) regressed observed prices (zero and nonzero observations) on time and household dummies, and used the least squares predictions to fill in prices when consumption is zero. In our case, least square regressions yielded prices for most commodities in the observed range, which are not high enough to force zero consumption. We therefore estimated each price equation as a censored model. As one would expect, the predicted price for nonconsuming households from the censored model is higher relative to that of Perali and Chavas' (2000) approach. An additional issue with prices is that most studies derive them as unit values, i.e., the ratio of observed expenditures and quantities (Dong, Shonkwiler, and Capps 1998). The unit values when introduced as independent variables in expenditure share equations create an endogeneity problem since they likely include (product) quality choices by households. As noted in the data section, prices used in this study are not unit values, but share weighted averages of sub-products' prices within a commodity, e.g., various cuts of beef.

The adding-up, homogeneity and symmetry (β_{ij}) conditions, as shown in Section II of the Appendix, are imposed in the estimation of the censored demand system. We tested whether or not household size, the educational levels of male and female members, and the education dummy of the household are additional shifters in the share and $\dot{C}$ equations. For space considerations, we do not report results of the chi-squared tests, which soundly rejected the joint restriction that the coefficients on household size, educational levels, and education dummy are equal to zero in the share and $\dot{C}$ equations. Furthermore, we tested our health-based demand system against the standard Marshallian demand system in equation (16) by jointly setting (i) the coefficients on $\dot{C}$ and C equal to zero in each of the share equations, and (ii) imposing instant adjustment, i.e., $a_2 = -1$, and all other coefficients equal to zero in the $\dot{C}$ equation. The calculated chi-squared test statistic (60,042) is well above the critical value (5.99, 2 degrees of freedom) soundly rejecting the standard Marshallian demand specification. Finally, our sensitivity analysis suggests that elasticities of demand with respect to fat, i.e., C effects on MFD product demand, reported in the next section become larger as α decreases, but price and expenditure elasticities, and adjustment rates remain about the same as with $\alpha = 0.013$. That is, as consumers begin to care more about tomorrow, their response to cumulative fat becomes larger. Changes to the decay rate and in computing initial fat level did not affect the results, but, as expected, higher decay rates led to lower responses to cumulative fat.

Results

The parameter estimates of the share and $\dot{C}$ equations are presented in table 2. Over two-thirds of the parameter estimates are significant at the 5% level. Note that the cheese share equation is dropped in our estimation, but its coefficients are deduced using the budget identity (Yen, Lin, and Smallwood 2003).

Table 3 presents the short-run price (compensated) and expenditure elasticities with their standard errors. They are evaluated at averages using conditional means of the respective censored dependent variables (Shonkwiler and Yen 1999). Uncompensated price elasticities are not presented due to space considerations. Own-price elasticities of all commodities, beef, pork, chicken, fish, cheese, and milk are negative and significant. They suggest that beef, pork, chicken, and milk demand are inelastic. The magnitude of these elasticities is similar to those reported by Yen, Lin, and Smallwood (2003) except for fish and cheese products. The own-price demand elasticity of fish is lower when evaluated at the average share of households which consumed fish (cheese), i.e., shares from nonzero observations. In the case of cheese, the large own-price demand elasticity is similar to the own-unit value elasticity in Dong and Kaiser's (2005) study on U.S. household cheese consumption. The magnitude of the own-price cheese (demand) elasticity may also be an outcome of deducing cheese equation parameters using the budget identity or if adding-up does not hold, situations similar to many household demand studies (e.g., Yen, Lin, and Smallwood 2003). Short-run cross price elasticities mostly suggest net substitution among the products, but

Table 2. Parameter Estimates of the Share and Cumulative Fat Motion Equation

Coefficients	Beef	Pork	Chicken	Fish	Milk	Coefficients	Ċ equation
Prices						Prices	
Beef	0.0127* (0.0016)	−0.0027* (0.0012)	0.0010 (0.0012)	0.0073* (0.0013)	0.0048* (0.0013)	Beef	−20.35 (16.98)
Pork	−0.0027* (0.0012)	0.0255* (0.0020)	−0.0002 (0.0013)	0.0030* (0.0015)	−0.0103* (0.0013)	Pork	47.82* (20.66)
Chicken	0.0010 (0.0012)	−0.0002 (0.0013)	0.0180* (0.0020)	−0.0045* (0.0014)	−0.0083* (0.0013)	Chicken	−71.82* (20.27)
Fish	0.0073* (0.0013)	0.0030* (0.0015)	−0.0045* (0.0014)	−0.0089* (0.0022)	0.0024 (0.0013)	Fish	69.49* (33.43)
Cheese	−0.0017 (0.0015)	−0.0068* (0.0016)	−0.0014 (0.0018)	0.0010 (0.0016)	0.0141* (0.0018)	Cheese	−110.19* (21.61)
Milk	0.0048* (0.0013)	−0.0103* (0.0013)	−0.0083* (0.0013)	0.0024 (0.0013)	0.0030 (0.0019)	Milk	−92.57* (22.95)
Expenditure	−0.0213* (0.0012)	−0.0085* (0.0009)	−0.0046* (0.0010)	−0.0002 (0.0008)	−0.0057* (0.0013)	Expenditure	798.83* (33.52)
Fat	−0.0053 (0.0069)	−0.0819* (0.0129)	−0.0398* (0.0159)	−0.0504* (0.0134)	−0.3492* (0.0128)	Fat	−0.0383* (0.0024)
Household Size	−0.0028* (0.0010)	−0.0042* (0.0010)	0.0013 (0.0013)	−0.0037* (0.0011)	0.0158* (0.0011)	Fat × household size	−0.0026* (0.0004)
Male Education	0.0015* (0.0007)	−0.0003 (0.0006)	0.0034* (0.0008)	0.0093* (0.0006)	0.0012 (0.0007)	Fat × male education	−0.0017* (0.0003)
Female Education	−0.0016* (0.0008)	0.0020* (0.0007)	0.0021* (0.0009)	0.0068* (0.0008)	0.0074* (0.0008)	Fat × female education	−0.0010* (0.0004)
Fat × Education Dummy	−0.0043 (0.0063)	0.1952* (0.0265)	0.1662* (0.0322)	0.1691* (0.0282)	0.8475* (0.0280)	Fat × education dummy	−0.0034* (0.0001)
Intercept	0.1515* (0.0049)	0.0723* (0.0043)	0.0754* (0.0048)	0.0131 (0.0063)	0.0987* (0.0079)	Intercept	−2,301.90 (1,692.79)
Shonkwiler & Yen Correction Factor	0.1111* (0.0035)	0.1463* (0.0027)	0.1528* (0.0034)	0.2105* (0.0034)	0.0743* (0.0033)		

Note: Standard errors in parentheses. Asterisks denote significance at the 5% level.
Education dummy takes value 1 when male and female education indexes are equal to or greater than 4.

Table 3. Short-Run and Long-Run Price and Expenditure Elasticities of Demand

	Quantity					
Item	Beef	Pork	Chicken	Fish	Cheese	Milk
	Short-Run					
Prices						
Beef	−0.675*	0.268*	0.005	0.423*	0.545*	0.314*
	(0.006)	(0.009)	(0.006)	(0.022)	(0.039)	(0.004)
Pork	0.126*	−0.687*	0.304*	0.193*	0.123*	0.112*
	(0.004)	(0.014)	(0.006)	(0.025)	(0.037)	(0.004)
Chicken	0.200*	0.198*	−0.770*	0.138*	0.375*	0.184*
	(0.004)	(0.009)	(0.009)	(0.023)	(0.043)	(0.004)
Fish	0.081*	0.078*	0.191*	−1.086*	0.139*	0.067*
	(0.004)	(0.011)	(0.007)	(0.037)	(0.037)	(0.004)
Cheese	0.035*	−0.005	0.055*	0.060*	−1.946*	0.084*
	(0.005)	(0.011)	(0.009)	(0.030)	(0.085)	(0.005)
Milk	0.335*	0.252*	0.005	0.381*	0.973*	−0.654*
	(0.004)	(0.008)	(0.005)	(0.019)	(0.045)	(0.006)
Expenditure	0.930*	0.960*	0.978*	0.996*	1.917*	0.983*
	(0.004)	(0.006)	(0.005)	(0.013)	(0.054)	(0.004)
	Long-Run					
Prices						
Beef	−0.675	0.271	0.004	0.431	0.454	0.320
Pork	0.126	−0.676	0.307	0.199	0.086	0.117
Chicken	0.200	0.206	−0.769	0.130	0.319	0.187
Fish	0.081	0.083	0.197	−1.072	0.127	0.070
Cheese	0.035	−0.003	0.054	0.062	−1.710	0.082
Milk	0.333	0.621	0.036	1.572	0.902	−0.649
Expenditure	0.930	0.960	0.970	1.022	1.621	1.005

Note: Standard errors are in parentheses. Asterisks denote significance at the 5% level.

some complementarities, e.g., pork and cheese, are observed. Expenditure elasticities are significantly positive and range from a low of 0.930 for beef to a high of 0.996 in the case of fish and the exception is cheese with a relatively large expenditure elasticity. In general, our price and expenditure elasticities are consistent with those reported in the literature (Hahn 1996; Kinnucan et al. 1995; Yen, Lin, and Smallwood 2003; Dong and Kaiser 2005).

Long-run (steady state) price and expenditure elasticities are reported in the second panel of table 3. They are similar to their short-run counterparts. The own-price demand and expenditure elasticities of cheese continue to remain large relative to those of other commodities.

Cumulative Fat's Adjustment Rates and Effects on Demand

The $\dot{C}$ equation is a function of cumulative fat (C), whose coefficient ($a_2 = (\alpha + \gamma) + \frac{\zeta}{\delta_2}$) de-termines the rate at which C adjusts to its optimal level. If a_2 were to equal −1 then the new cumulative fat level in time period $t + 1$, C_{t+1} is independent of the C_t. Hence, restricting $a_2 = -1$ is equivalent to the instantaneous adjustment of cumulative fat level. Recall that we rejected instantaneous adjustment (static model) in favor of the dynamic demand system. In addition, we tested the hypothesis that the adjustment rate of cumulative fat also depends on the size and/or education level of the household. So, slope dummies, interacting C with size, male and female education, and the education dummy are introduced into the $\dot{C}$ equation. The interaction terms allowed us to test whether or not larger or more educated households have a different rate of adjustment of cumulative fat.

Table 4 presents the mean and 95% confidence interval for the rate of adjustment of cumulative fat to its optimal level in the base sample (ignoring interaction terms) and its three variations due to household size and/or education level. The chi-squared test statistic in the last column corresponds to the

Table 4. Adjustment Rates of Cumulative Fat, 95% Confidence Intervals

Sample	Lower (Percentage)	Mean (Percentage)	Upper (Percentage)	χ^2 Statistic for Instant Adjustment
Base sample	−2.91	−2.53	−2.14	30,700
Adjustment rates for				
Larger households	−4.38	−3.26	−2.14	30,069
Highly educated households				
Male	−5.02	−3.90	−2.78	33,524
Female	−4.79	−3.65	−3.15	35,820
Larger and highly educated households	−5.74	−4.63	−3.53	28,044

Note: Education dummy takes value 1 when male and female education indexes are equal to or greater than 4.

restriction that $a_2 = -1$ for the base, and the restriction that the sum of a_2 and the coefficient on the interaction term equals −1 for the three variations. For instance, if a_2^H is the coefficient of the interaction between cumulative fat (C) and household size, then the instantaneous adjustment restriction is $a_2^H + a_2 = -1$. For the base sample (all 250 households) and the three variations, we reject instantaneous adjustment of cumulative fat at the 5% significance level. The mean adjustment rate of −2.53% per month translates into −30.3% per year in the base sample. For instance, if households desired to reduce the steady-state fat level by 50%, it would take approximately two years to achieve that reduction. The adjustment rate is higher for larger households (–3.26% per month or −39.1% per year) and for highly educated male or female households (–3.90 or 3.65% per month or −46.8 or 43.8% per year, respectively). When accounting for household size and education, the adjustment rate is −4.63% per month or −55.6% per year. These results imply that certain factors preclude consumers from instantaneously adjusting their fat intake, which we termed earlier as "adjustment benefits."

The steady-state elasticities of demand with respect to fat or the effects of cumulative fat (C) on demand for meat and dairy products and respective standard errors are reported in table 5. Unlike adjustment rates, we present only one additional set of elasticities using the educated dummy. The household size and male/female educational differences did not significantly alter the elasticities of demand with respect to fat and hence, they are not reported. In the base sample, these fat elasticities indicate that a 1% increase in C would significantly reduce demand for all MFD products except cheese. While we do not have a priori expectations for the signs of fat elasticities, some of the results can be driven by habit formation and technological change altering the proportion of bads in MFD products, e.g., fat content. However, educated households, which adjust faster to an increase in cumulative fat level, exhibit different responses relative to the base sample. For educated households, the elasticities of demand with respect to fat are negative for beef and cheese, but only the cheese elasticity is significant at the 5% level. Most notable is the pronounced increase (decrease) in the demand for fish (cheese)

Table 5. Elasticities of Demand with Respect to Fat

Commodity	Base Sample		Educated Households	
	Elasticities	Standard Error	Elasticities	Standard Error
Beef	−0.0032*	0.0013	−0.0006	0.0011
Pork	−0.0103*	0.0023	0.0145*	0.0029
Chicken	−0.0034*	0.0003	0.0110*	0.0035
Fish	−0.0150*	0.0002	0.0359*	0.0031
Cheese	0.2180*	0.0005	−0.3564*	0.0012
Milk	−0.0185*	0.0002	0.0268*	0.0003

Note: Asterisks denote significance at the 5% level.

products due to a 1% increase in *C* among educated households, which is consistent with the recommendations of the scientific studies noted earlier. Although a direct comparison with other studies is not feasible, these results are consistent with the health-information effects on food demand in Chern, Loehman, and Yen (1995), and Kim and Chern (1999). Kinnucan et al. (1995) found switching from red to white meat products in U.S. food consumption due to health concerns, while Dong and Kaiser (2005) showed that education negatively impacts households' cheese purchases.

Summary and Conclusions

We proposed a dynamic approach to incorporate health variables in the demand for MFD products. It involved a two-step optimization problem, where the first step consists of a utility maximization problem with two constraints: an expenditure constraint and a fat intake constraint. Here, consumers earn positive utility from the consumption of foods (goods), even those with high fat content, but earn negative utility from their cumulative fat level (bads) in the body. Therefore, consumers face not only expenditure constraints but also constraints on the amount of fat they are willing to absorb each time period. The solution to the first-step problem is an IUF with properties not unlike those of the standard IUF, but fat intake and the cumulative fat level are arguments of the IUF.

In the second step consumers maximize utility over time by regulating their fat intake in order to control the cumulative fat level. The choice on fat intake is presented as a dynamic optimization problem, which leads us to a DIUF. Using the duality properties of the DIUF we derive dynamic consumer demand functions with fat intake and cumulative fat as arguments in addition to prices and expenditures.

A second-order approximation of the DIUF translated the dynamic demand functions into expenditure shares and also provided an equation of motion for cumulative fat. They are estimated as a censored system using data on 250 U.S. households on a monthly basis between December 1997 and January 2001, which are obtained from the ACNH database. The products included in our estimation are beef, pork, chicken, fish, milk, and cheese. The fat content of these products are taken from a recent report from the U.S. Department of Agriculture's Agricultural Research Service to derive fat intake and cumulative fat levels over

time. Various specification tests and residual analyses validated our estimated censored demand system.

We find that consumers' do not instantaneously adjust their cumulative fat level to its optimum, but the rate of adjustment depends on households' size and education. The elasticities of demand with respect to fat indicate that an increase in cumulative fat level shifts consumption in favor of white meat or dairy products and against red meat products, but significant differences exist in the responses of educated and other households. Educated households show more diet discipline by quickly moving to their desired fat levels. The adjustment rates of cumulative fat and the elasticities of demand with respect to fat indicate that consumers consciously incorporate health attributes such as fat content in their food choices. Therefore, food demand studies should also consider the underlying health decisions and risks faced by consumers. In this context, our dynamic approach provides an understanding of how consumers manage an important health attribute, i.e., accumulated body fat. More importantly, we guide the choice of health variables to include in demand estimation using dynamic duality theory. Substitution possibilities, education, and the publicly available, health-related information are important in managing and adjusting fat levels, which are well reflected in the demand responses of educated households in our sample. It is likely that some consumers manage more than one "bad." A similar modeling of calorie or cholesterol management and its adjustment along with efforts to develop databases on individuals will likely aid in a better understanding of dietary choices and human health including obesity.

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Appendix

Properties of the Dynamic Indirect Utility (Value) Function

The DIUF is homogenous of degree zero in prices and income if

(A1.1) $$\sum_{i=1}^{n} V_{p_i} p_i + V_E E = 0.$$

Using the relation in equation (4), the expression in (A1.1) becomes

(A1.2a)

$$\sum_{i=1}^{n} (\psi_{p_i} + V_{Cp_i} \dot{C}) \frac{p_i}{\alpha} + (\psi_E + V_{CE}\dot{C}) \frac{E}{\alpha} = 0$$

or

(A1.2b) $$\frac{1}{\alpha} \left(\sum_{i=1}^{n} \psi_{p_i} p_i + \psi_E E \right)$$

$$+ \frac{1}{\alpha} \left(\sum_{i=1}^{n} V_{Cp_i} p_i + V_{CE}E \right) \dot{C} = 0.$$

The first term in equation (A1.2b) equals zero by homogeneity of the static IUF. Therefore the DIUF is homogenous of degree zero in prices and expenditures if

(A1.3a)

$$\sum_{i=1}^{n} V_{p_i} p_i + V_E E = \frac{1}{\alpha} \left(\sum_{i=1}^{n} V_{Cp_i} p_i + V_{CE}E \right) \dot{C} = 0$$

or if

(A1.3b)

$$\sum_{i=1}^{n} (\alpha V_{p_i} - V_{Cp_i} \dot{C}) p_i + (\alpha V_E - V_{CE}\dot{C})E = 0.$$

From equation (7) we know that

(A1.4) $$\alpha V_{p_i} - V_{Cp_i}\dot{C} = \psi_{p_i} \quad \forall i = 1, 2, \ldots, n$$

$$\alpha V_E - V_{CE}\dot{C} = \psi_E.$$

Substituting (A1.4) into (A1.3b) gives

(A1.4) $$\sum_{i=1}^{n} \psi_{p_i} p_i + \psi_E E = 0$$

which must hold by the homogeneity condition of the static IUF. Therefore, the DIUF inherits the static IUF property of homogeneity of degree zero in prices and expenditure. Similarly, the DIUF can be shown to be decreasing in cumulative fat, convex in output prices, and concave in expenditures given similar properties of the static IUF (Lemma 1, part b, Epstein 1981, p. 86).

Deriving the Linear Share Equation

Adding up, i.e., shares sum to one, holds if the sum of the numerators of each share equation equals the denominator.

(A2.1)

$$s_i = \frac{\alpha \left(\beta_i + \sum_{j=1}^{n} \beta_{ij}\tilde{p}_j + \mu_i C + \pi_i \tilde{E} \right) - \mu_i \dot{C}}{\alpha \left(1 + \sum_{i=1}^{n} \pi_i \tilde{p}_i \right)}$$

$$= \frac{\left(\beta_i + \sum_{j=1}^{n} \beta_{ij}\tilde{p}_j + \mu_i C + \pi_i \tilde{E} \right) - \frac{\mu_i}{\alpha}\dot{C}}{\left(1 + \sum_{i=1}^{n} \pi_i \tilde{p}_i \right)}.$$

Since $\sum_{i=1}^{n} s_i = 1$

(A2.2)

$$\sum_{i=1}^{n} \left\{ \alpha \left(\beta_i + \sum_{j=1}^{n} \beta_{ij}\tilde{p}_j + \mu_i C + \pi_i \tilde{E} \right) - \mu_i \dot{C} \right\}$$

$$= \sum_{i=1}^{n} \alpha \left(1 + \sum_{i=1}^{n} \pi_i \tilde{p}_i \right).$$

From equation (15), we imposed $\sum_{i=1}^{n} \beta_i = 1$; $\sum_{i=1}^{n} \beta_{ij} = \sum_{j=1}^{n} \beta_{ij} = \sum_{i=1}^{n} \mu_i = \sum_{i=1}^{n} \pi_i = 0$. Therefore, $\alpha(1 + \sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij}\tilde{p}_j) = \alpha(1 + \sum_{i=1}^{n} \times \pi_i \tilde{p}_i)$. Note that the $\tilde{p}$'s in the double summation is indexed over j only. So, $\alpha(1 + \sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij}\tilde{p}_j) = 0$ meaning, $\sum_{i=1}^{m} \pi_i p_i = 0$. As a result the denominator of (A2.1) reduces to 1. The nonlinear share equation has now become a linear function of prices, expenditure, and cumulative fat.